International Journal of Mechanical and Production Engineering Research and Development (IJMPERD)
ISSN (P): 2249-6890; ISSN (E): 2249-8001
Vol. 9, Issue 4, Aug 2019, 831-838


# EDM PARAMETERS OPTIMIZATION ON TOOL WEAR RATE USING ADVANCED OPTIMIZATION OF TITANIUM ALLOY

**NEERAJ AGARWAL[1], NITIN SHRIVASTAVA[2] & M. K. PRADHAN[3]**

*[1,2]University Institute of Technology, Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal, India*

*[3]Maulana Azad National Institute of Technology, Bhopal, India*

***ABSTRACT***

***Electrical Discharge Machining (EDM) is the most popular unconventional machining processes (UMP) in modern industries. EDM requires a low initial investment and used to machine difficult-to-cut and to machine complex shapes. There is sparking takes place between workpiece and tool, and the machined surface has an exact replica of tools. Due to sparking, material is removed from workpiece and some material is also removed from the tool surface, thus resulting distortion of the tool there. This further leads to affect the quality of machined surface, hence it is required to minimize tool wear rate (TWR). This paper is based on parameter optimization to minimized TWR. Thirty experiments were carried out as per the design of experiments using response surface methodology, within the selected range of various input variables. The regression model is developed for TWR. An advanced optimization Jaya Algorithm used to optimize TWR model. A predictable ANN model is also developed to validate the optimum result.***

***KEYWORDS: Electrical Discharge Machining, Jaya Algorithm, Advanced Optimization & TWR***

**Received**: May 11, 2019; **Accepted**: May 31, 2019; **Published**: Jul 11, 2019; **Paper Id.**: IJMPERDAUG201985

**Original Article**

## 1. INTRODUCTION

Nowadays, with the advancement of technology, there is a need for machine, very hard material which is very difficult (sometimes not possible) to a machine with the conventional machining process. Unconventional machining process like ultrasonic machining (USM), electrical discharge machining (EDM), abrasive jet machining, electrochemical machining (ECM), electron beam machining, laser beam machining (LBM), ion beam machining etc. [1], are used to machine extremely hard materials like composites, ceramics andsuper alloys.

EDM is the most popular non-conventional machining process. EDM is widely used in the aerospace industry to machine super alloy, Titanium alloy, etc. Ho et al. [2] reviewed the effect of electrical and non-electrical control input parameter to the quality measures like material removal rate (MRR), tool wear rate (TWR) and surface roughness (Ra). They also discussed various manufacturing issuesand electrode design. Abbas et al. [3] presented the recent research trend in wire EDM, die-sinking EDM, EDM with water dielectric, dry EDM, Effect of powder mixed additives to EDM process, ultrasonic EDM. Garg et al. [4] did a review ofwire electrical discharge machining (WEDM), sinking EDM on metal matrix composite (MMC). Kumar et al. reviewed of research work carried in the field of additive mixed EDM process [5] and application of powder additives on imparting desired surface finish to the machined surface [6].

There are so many input factors for EDM machining, hence optimization is required to optimize variousperformance measures like MRR to be maximized, surface roughness (Ra) to be minimized, tool wear rate

(TWR) to be minimized. As numbers of input parametersincreases, optimization difficulty level and complication increases. Classical optimization methods become insignificant to solve theproblem hence need for advanced optimization arises. Nowadays, advanced optimization is more popular because of its capability to solve the most complex problem. Advancedoptimization based on metaheuristic becomes more popular [7] in the field of optimization. Rao developed Jaya Algorithm in 2016, which are population-based advanced optimization techniques [8]. In this paper, a computer program is developed to optimize the tool wear rate (TWR).

## 2. ELECTRIC DISCHARGE MACHINING

### 2.1 Principle of EDM

EDM is an unconventional machining process, which is used to machine difficult to cut material and to machine complex shape material [1]. EDM used to machine electrically conductive material as workpiece, which is submerged in a dielectric fluid. There is sparking takes place between the workpiece and an electrically conductive electrode due to applying a pulsating voltage across them. Due to this, sparking local temperature rises to $8000^0$ C- $10000^0$ C. Such a high temperature will melt and or vaporize the material. The mechanism of EDM is shown in Figure 1.

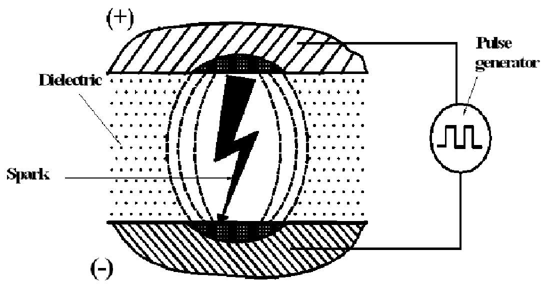


**Figure 1: Systematic Diagram of EDM**

## 3. EXPERIMENTAL DETAILS

Titanium alloy is selected as workpiece and copper rod of 10 mm diameter is selected as a tool. Software package Minitab 18 is used the design of experiment using response surface methodology. Experiments were carried out at Electronica CNC EDM machine. Peak current (Ip), Voltage (V), Pulse on time (Ton), Duty factor (t) is selected as control parameter and Tool Wear Rate (TWR) as output. Total of thirty experiments has been done. Machining time is kept constant for 30 minutes. The copper tool is measured before and after every experiment using precision digital weight balance of 0.1 mg resolution. Quality variable TWR measured using the following formula

$$TWR = \frac{Tfw - Tiw}{Tp} \quad (1)$$

Where Tfw = Final weight of the tool, Tiw = Initial weight of the tool, Tp = Total time period of machining.

Response surface regression model is developed using response surface methodology, using software package Minitab 18. After removal ofthe nonsignificant term following, the model of TWRis developed.

$$\begin{aligned} \text{TWR (mg/min)} = {} & -0.529 + 0.3158\ Ip - 0.00001\ V - 0.01235\ Ton + 0.1048\ t + 0.000039\ Ton{*}Ton \\ & - 0.00386\ t{*}t - 0.000811\ Ip{*}V - 0.000497\ Ip{*}Ton - 0.00941\ Ip{*}t + 0.000024\ V{*}Ton \\ & + 0.000228\ Ton{*}t \end{aligned} \quad (2)$$

**Table 1: Input Parameter Range**

| Parameter | Level 1 | Level 2 | Level 3 |
|---|---|---|---|
| Ip (Ampere) | 4 | 6 | 8 |
| V (Volt) | 40 | 70 | 100 |
| Ton (μ seconds) | 50 | 100 | 150 |
| t (Duty factor setting) | 8 | 12 | 16 |

**Table 2: Experimental Layout for the Response Surface**

| Ip | t | V | Ton | TWR mg/min |
|---|---|---|---|---|
| 4 | 8 | 40 | 50 | 0.3283 |
| 4 | 8 | 40 | 150 | 0.1167 |
| 4 | 8 | 100 | 50 | 0.2917 |
| 4 | 8 | 100 | 150 | 0.1000 |
| 4 | 12 | 70 | 100 | 0.0727 |
| 4 | 16 | 40 | 50 | 0.3567 |
| 4 | 16 | 40 | 150 | 0.0817 |
| 4 | 16 | 100 | 50 | 0.2050 |
| 4 | 16 | 100 | 150 | 0.0767 |
| 6 | 8 | 70 | 100 | 0.3450 |
| 6 | 12 | 40 | 100 | 0.4067 |
| 6 | 12 | 70 | 50 | 0.6833 |
| 6 | 12 | 70 | 100 | 0.3655 |
| 6 | 12 | 70 | 100 | 0.3717 |
| 6 | 12 | 70 | 100 | 0.3883 |
| 6 | 12 | 70 | 100 | 0.3533 |
| 6 | 12 | 70 | 100 | 0.3517 |
| 6 | 12 | 70 | 100 | 0.3626 |
| 6 | 12 | 70 | 150 | 0.2200 |
| 6 | 12 | 100 | 100 | 0.2667 |
| 6 | 16 | 70 | 100 | 0.2417 |
| 8 | 8 | 40 | 50 | 1.1367 |
| 8 | 8 | 40 | 150 | 0.5500 |
| 8 | 8 | 100 | 50 | 0.9000 |
| 8 | 8 | 100 | 150 | 0.3217 |
| 8 | 12 | 70 | 100 | 0.6056 |
| 8 | 16 | 40 | 50 | 0.7367 |
| 8 | 16 | 40 | 150 | 0.3183 |
| 8 | 16 | 100 | 50 | 0.2750 |
| 8 | 16 | 100 | 150 | 0.2567 |

### 3.1 Artificial Neural Network Model for Tool Wear Rate

A predictable ANN model [9] is developed in this research, based on the design of experiments. Totally, thirty experiments were conducted, which are input to the ANN Model. ANN Model consists of (1) Input Layer (2) Hidden Layersand (3) Output Layer. The Inputs are multiplied by a respective weight and then summation into a hidden layer.

After various experimentation, it is found that total of five neurons required with log sigmoid function for hidden layer, and pure linear activation function for the output layer generates better predictable ANN model. ANN model is developed to verify optimum result produced by Jaya Algorithm.

## 4. OPTIMIZATION OF TOOL WEAR RATE (TWR)

The objective is to minimize TWR. Jaya algorithm is used to optimize the optimization of TWR. Flow chart of Jaya Algorithm as following

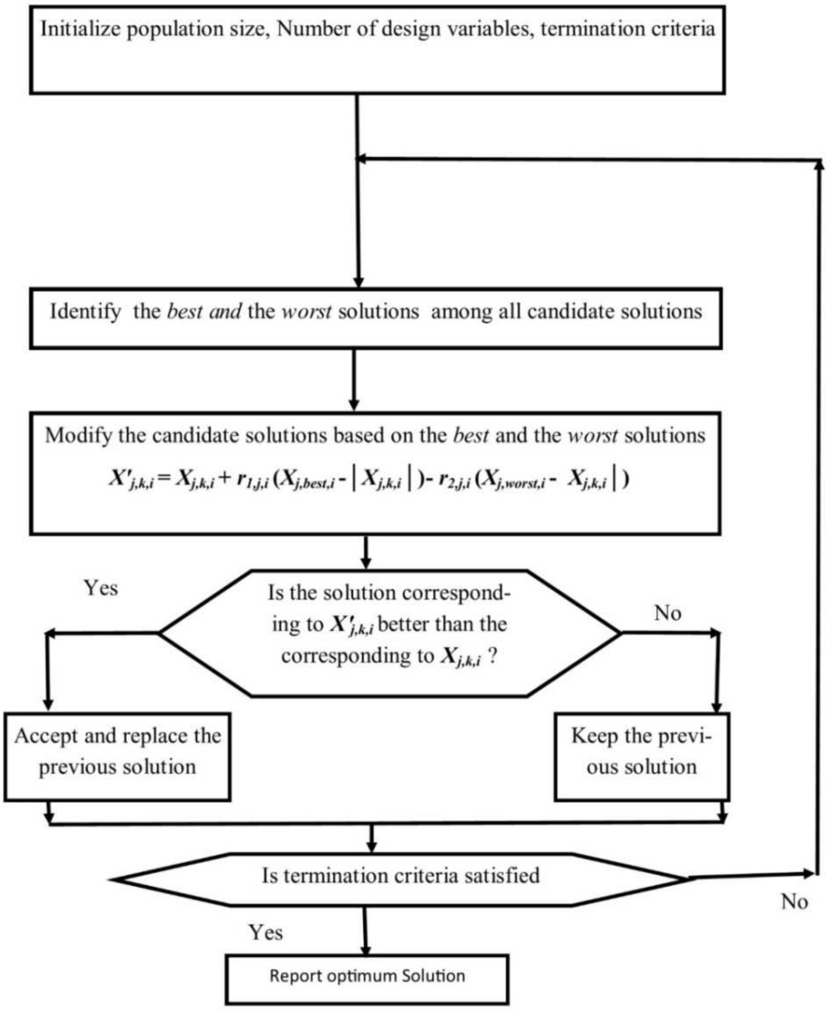


**Figure 2: Flow Diagram of Algorithm**

**Step 1:** consider population size 5, generate random withinthe upper bound and lower bound of design variables.

**Table 3: Initial Population**

| Candidate | Ip | Ton | t | V | TWR |
|---|---|---|---|---|---|
| 1 | 7.8497 | 81.3736 | 14.3767 | 57.1105 | 0.5463 |
| 2 | 4.0596 | 51.3022 | 13.4500 | 99.3366 | 0.2652 |
| 3 | 4.3766 | 66.2207 | 13.7163 | 95.9561 | 0.2267 |
| 4 | 5.3149 | 94.3939 | 11.6732 | 67.6914 | 0.3074 |
| 5 | 5.2223 | 126.6770 | 15.3541 | 94.2953 | 0.1272 |

**Step 2:** Consider random number r1=0.3865, r2=0.6030 and recalculate all design variables as per following formula (if the new value of design variable beyond the upper limit, then assign asan upper limit. If the new value of design variable is below the lower limit, then assigns lower limit).

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i}(X_{j,best,i} - |X_{j,k,i}|) - r_{2,j,i}(X_{j,worst,i} - |X_{j,k,i}|)$$

It is observed from Table 1 that candidate 5 has best solution (minimum TWR better) Ip-best=5.2223, Ton-best=126.6770, t-best=15.3541, V-best=94.2953. Candidate 1 has worst solution hence Ip-worst=7.8497, Ton-worst=81.3736, t-worst=14.3767, V-worst=57.1105

Ip-candidate 1= 7.8497+0.3865*(5.2223-│7.8497│)-0.6030*(7.8497-│7.8497│) = 6.8343

Ip-candidate 2= 4.0596+0.3865*(5.2223-│4.0596│)-0.6030*(7.8497-│4.0596│) = 2.2235=4 (lower bound)

Ip-candidate 3.= 4.7366+0.3865*(5.2223-│4.7366│)-0.6030*(7.8497-│4.7366│) = 3.0471 =4 (lower bound)

Ip-candidate 4= 5.3149+0.3865*(5.2223-│5.3149│)-0.6030*(7.8497-│5.3149│) = 3.7506 = 4 (lower bound)

Ip-candidate 5= 5.2223+0.3865*(5.2223-│5.2223│)-0.6030*(7.8497-│5.2223│) = 3.6379 = 4 (lower bound)

Ton candidate 1= 81.3736 +0.3865* (126.6770-│81.3736│)-0.6030*(81.3736-│81.3736│)= 98.8812

tfor candidate 1 = 14.3767+0.3865 * (15.3541-│14.3767│)-0.6030*(14.3767-│14.3767│)=14.7544

V candidate 1 = 57.1105+ 0.3865*(94.2953-│57.1105│)-0.6030*(57.1105-│57.1105│) = 71.4807

Rest calculation ae same

**Table 4: New Values of the Variables and Objective Function Value**

| Candidate | Ip | Ton | t | V | TWR |
|---|---|---|---|---|---|
| 1 | 6.8343 | 98.8812 | 14.7544 | 71.4807 | 0.316 |
| 2 | 4 | 62.9056 | 13.6271 | 100 | 0.206 |
| 3 | 4 | 80.4467 | 13.951 | 100 | 0.1424 |
| 4 | 4 | 114.7273 | 11.4716 | 84.353 | 0.1229 |
| 5 | 4 | 150 | 15.9436 | 100 | 0.1304 |

**Step 3:** Compare Table 3 and Table 4 for each candidate for TWR and select the candidate which have lower value of TWR, candidate 1 from Table 4, candidate 2 from Table 4, candidate 3 from Table 4, candidate 4 from Table 4, candidate 5 from Table 3 selected and inserted into Table 5.

**Table 5: Updated Values of Variables at the End of the First Iteration**

| Candidate | Ip | Ton | t | V | TWR |
|---|---|---|---|---|---|
| 1 | 6.8343 | 98.8812 | 14.7544 | 71.4807 | 0.316 |
| 2 | 4 | 62.9056 | 13.6271 | 100 | 0.206 |
| 3 | 4 | 80.4467 | 13.951 | 100 | 0.1424 |
| 4 | 4 | 114.7273 | 11.4716 | 84.353 | 0.1229 |
| 5 | 5.2223 | 126.6770 | 15.3541 | 94.2953 | 0.1272 |

**Step 4:** Iteration 1 is over now. Table 5 would be input as the input to the second iteration. Now consider random number r1=0.5603 and r2=0.8458 for second iteration.

**Table 6: New Values of the Variables and Objective Function Value for the Second Iteration**

| Candidate | Ip | Ton | t | V | TWR |
|---|---|---|---|---|---|
| 1 | 5.2462 | 107.7601 | 12.915 | 78.6933 | 0.2261 |
| 2 | 4 | 61.5128 | 11.4658 | 100 | 0.2454 |
| 3 | 4 | 84.0622 | 11.8822 | 100 | 0.1616 |
| 4 | 4 | 128.1306 | 8.6949 | 95.2409 | 0.0664 |
| 5 | 4 | 143.4922 | 13.686 | 100 | 0.1427 |

**Step 5:** Compare Table 5 and Table 6 for each candidate for TWR, and select the candidate which has lower value of TWR, candidate 1 from Table 6, candidate 2 from Table 5 candidate 3 from Table 5, candidate 4 from Table 6, candidate 5 from Table 5 selected and inserted into Table 7.

**Table 7: Updated Values of Variables for the Second Iteration**

| Candidate | Ip | Ton | t | V | TWR |
|---|---|---|---|---|---|
| 1 | 5.2462 | 107.7601 | 12.915 | 78.6933 | 0.2261 |
| 2 | 4 | 62.9056 | 13.6271 | 100 | 0.2060 |
| 3 | 4 | 80.4467 | 13.951 | 100 | 0.1424 |
| 4 | 4 | 128.1306 | 8.6949 | 95.2409 | 0.0664 |
| 5 | 5.2223 | 126.677 | 15.3541 | 94.2953 | 0.1272 |

**Step 6:** Now the second iteration is over. Table 7 would be input to iteration 3. Repeat same procedure (step 4 and step 5) for 100 iterations. Report optimal solution.

**Table 8: Result Iteration Wise Best Result (Convergence of TWR)**

| Sr No | Ip | Ton | t | V | TWR (mg/ minutes) |
|---|---|---|---|---|---|
| 1 | 5.2223 | 126.677 | 15.3541 | 94.2953 | 0.1272 |
| 2 | 4 | 128.1306 | 8.6949 | 95.2409 | 0.0664 |
| 3 | 4 | 141.6428 | 8 | 100 | 0.0489 |
| 4 | 4 | 141.6428 | 8 | 100 | 0.0489 |
| 5 | 4 | 138.8711 | 8 | 100 | 0.0466 |
| 6 | 4 | 138.0114 | 8 | 100 | 0.0460 |
| 7 | 4 | 138.0114 | 8 | 100 | 0.0460 |
| 8 | 4 | 138.0114 | 8 | 100 | 0.0460 |
| 9 | 4 | 138.0114 | 8 | 100 | 0.0460 |
| 10 | 4 | 130.3589 | 8 | 100 | 0.0433 |
| 11 | 4 | 150 | 8 | 40 | 0.0387 |
| 12 | 4 | 150 | 8 | 40 | 0.0387 |
| 13 | 4 | 150 | 8 | 40 | 0.0387 |
| 14 | 4 | 150 | 8 | 40 | 0.0387 |
| 15 | 4 | 150 | 8 | 40 | 0.0387 |
| 16 | 4 | 150 | 8 | 40 | 0.0387 |
| 17 | 4 | 148.6359 | 8 | 40 | 0.0386 |
| 18 | 4 | 147.9602 | 8 | 40 | 0.0385 |
| 100 | 4 | 147.9602 | 8 | 40 | 0.0385 |

### 4.1 Optimization with Teaching Learning Based Optimization Algorithm (TLBO)

The TWR is also optimized with TLBO; and got optimum parameter Ip=4, Ton=147.9602, t=8 and V=40 with minimized TWR as 0.0385 mg/minutes. TLBO requires 109 iterations to optimizing.

### 4.2 Optimization with Minitab

Commercial software package Minitab 18 used to optimize TWR using response surface methodology and response optimizer produces optimized values as Ip=4, Ton=150, t=8 and V=40 with minimized tool wear as 0.0399 mg/minutes.

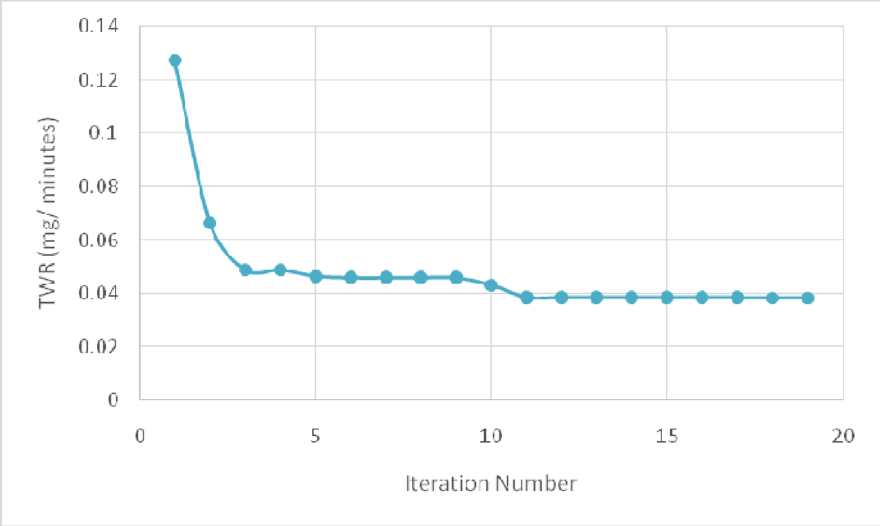


**Figure 3: Convergence Graph of TWR**

## 5. RESULTS

Commercially available software Minitab18 produces 0.0399 mg/minutes. Jaya algorithm achieved the result in just 17th iteration as minimized TWR as 0.0385 mg/minutes, which is better than Minitab optimization. TLBO also achieved the same result as Jaya algorithm, but took 109 iterations which are much larger as 18 iterations of Jaya Algorithm. Further, Jaya algorithm is simpler to implement and converges result faster than TLBO. Hence, Jaya Algorithm is a better choice. It is concluded that Jaya Algorithm produced the best optimum result.

ANN Model predict TWR=0.0387mg/minutes at Ip=4, Ton=147.9602, t=8, and V=40; which are very close to result produced by Jaya Algorithm. A predictable ANN model validates the model developed by commercial software Minitab 18 as equation (2).

## 6. CONCLUSIONS

It can be concluded from the above discussion that using Jaya Algorithm findsthe optimum result in just 18 iterations. The same optimization is done by software package Minitab 18 report optimum TWR as 0.0399mg/seconds. Same optimization problem is solved by TLBO algorithm which reports TWR as 0.0385 mg/min. Jaya Algorithm has great potential to solve engineering optimization. Theresults are also validated by ANN Model.

***REFERENCES***

1. *V.K. Jain, Advanced Machining Processes, Allied Publishers, New Delhi, 2002.*
2. *Ho K.H.; Newman S.T. State Of The Art Electrical Discharge Machining (Edm). International Journal Of Machine Tools And Manufacture 2003, 43, 1287-1300.*
3. *N.M. Abbas, D.G. Solomon, M.F. Bahari, A Review On Current Research Trends In Electrical Discharge Machining (Edm), International Journal Of Machine Tools And Manufacture 47 (2007) 1214-1228.*
4. *R.K. Garg, K.K. Singh, A. Sachadeva, V. Sharma, K. Ojha, Review Of Research Work In Sinking Edm And Wedm On Metal Matrix Composite Materials, International Journal Of Advanced Manufacturing Technology 50 (2010) 611-624.*

5. *A. Kumar, S. Maheshwari, C. Sharma, N. Beri, Research Development In Additives Mixed Electrical Discharge Machining (Aedm): A State Of Art Review, Materials And Manufacturing Processes 25 (2010) 1186–1197.*

6. *N. Beri, S. Maheshwari, C. Sharma, A. Kumar, Technological Advancement In Electric Discharge Machining With Powder Metallurgy Processed Electrodes: A Review, Materials And Manufacturing Processes 25 (2010) 1166–1180.*

7. *Xin-She Yang, Review Of Metaheuristics And Generalized Evolutionary Walk Algorithm, Int. J. Bio-Inspired Computation,3(2), 77-84 (2011).*

8. *Erfan, O. S. A. M. A., El-Nasr, A., Ba, A., & Al-Mufadi, F. (2014). Erosion-Corrosion Behavior Of Aa 6066 Aluminum Alloy. Ijme, 3, 15-24.*

9. *Rao R. Venkata ,Jaya: A Simple And New Optimization Algorithm For Solving Constrained And Unconstrained Optimization Problems, International Journal Of Industrial Engineering Computations, 7,19{34 (2016)*

10. *Shrivastava Pankaj Kumar, Dubey Avanish Kumar, Modelling And Multi-Objective Optimisation Of Eddg Process Using Hybrid Ann-Ga Approach, International Journal Of Abrasive Technology, 7(3), 226-245 (2016)*

11. *Disclaimer: Authorsdeclares That This Research Paper Has Been Neither Published Nor Submitted For Publication, In Whole Or In Part, Either In A Serial, Professional Journal Or As A Part In A Book Which Is Formally Published And Made Available To The Public.*